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Impacts of climate change on groundwater level and irrigation cost in a groundwater dependent irrigated region

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ABSTRACT

The objective of the present study was to assess the impacts of climate change on irrigation cost in a groundwater dependent irrigated region in northwest Bangladesh. An ensemble of general circulation model (GCMs) were used for the projection of climate, an empirical hydrological model based on support vector machine (SVM) was used to simulate groundwater level from climatic variables, and a multiple-linear regression (MLR) model was used to estimate the irrigation cost due to the changes in groundwater level. The results revealed a declination of average groundwater level in the study area in the range of 0.45 – 01.19 m, 0.55–1.79 m, and 0.76–2.71 m under three representative concentration pathways (RCP) scenarios namely, RCP2.6, RCP4.5 and RCP8.5, respectively and therefore, an average increase in irrigation cost in the range of 1.61 to 9.82 USD/hectare at 95% confidence level. The maximum declination of groundwater level was projected in the northeast part of the study area in the range of 2.23–4.12 m by the GCM MIROC-ESM-CHEM which might cause an increase of irrigation cost in the range of 8.07 to 14.79 USD/hector. The study concludes that the impact of climate change-induced fluctuations in groundwater level on crop production cost is much less compared to other costs, but it may be significant in locations where groundwater level is declining fast.

1. Introduction

Groundwater is one of the primary sources of irrigation and food production in many countries of the World (Shahid et al., 2015; Siebert et al., 2010; Treidel et al., 2012). Despite its huge significance, groundwater resources are heading for a crisis in many regions mainly due to the huge exploitation of groundwater to extend irrigated agriculture to feed the growing population(Gandhi and Bhamoriya, 2011; Pengra, 2012). It is anticipated that climate change will pose another major threat to groundwater resources in the near future. Studies from different parts of the world show that increased temperature and changing rainfall patterns due to climate change will significantly affect groundwater recharge and accessibility (Davidson and Yang, 2007; Ranjan et al., 2006; Shahid et al., 2017; Shahid and Hazarika, 2010; Treidel et al., 2012). The lowering of the groundwater table due to changes in precipitation patterns and rises in temperature may reduce well yield and increase pumping cost, which may seriously affect the livelihood of farmers in the regions where groundwater is used as the major source of irrigation (Salem et al., 2017b). Mitigation of climate change impacts on groundwater resources to limit irrigation cost and ensure farmers' profits might be a major challenge in the near future, particularly in agricultural-based developing countries.

A number of studies have been conducted to assess climate change impacts on groundwater level (Davidson and Yang, 2007; Ranjan et al., 2006; Treidel et al., 2012), irrigation demand (Garrote et al., 2015; Shahid, 2011; Wang et al., 2016), and irrigation cost (Mulangu and Kraybill, 2015; Nelson et al., 2010). However, only a few studies have been conducted to assess the impact of declining groundwater level on irrigation cost (Kovacs and West, 2016; Medellín-Azuara et al., 2015; Narayanamoorthy, 2015; Nayak et al., 2015; Salem et al., 2017a; Srivastava et al., 2017). The majority of the studies was on economic assessment of declining groundwater level due to over exploitation (Narayanamoorthy, 2015). A few of studies mentioned changes in irrigation cost due to global warming induced changes in groundwater level. Shahid (2011) indicated that declination of groundwater level due to climate change would increase irrigation cost in Northwest Bangladesh. Nayak et al., (2015) assessed the impacts of different adaption measures to mitigate climate change impacts on irrigation cost. However, no study has been conducted to assess the possible changes in irrigation cost of groundwater-dependent irrigated crop for

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different climate change scenarios. As groundwater is the major source of irrigation in many developing countries, understanding the impact of climate change on farmers' profits in a groundwater dependent irrigated region is very impotent. Furthermore, it is important for decision making towards adaptation and mitigation.

The GCM simulations of climate change fail to provide reliable information on spatial scales below about 200 km and therefore, it is important to downscale coarse resolution GCM simulated climatic variables to local scales for impact assessment (Su et al., 2016). Climate downscaling methods can be broadly classified into two major groups namely, (i) dynamical or physical downscaling, where high-resolution Regional Climate Models (RCMs) are employed (Gao et al., 2016; Laprise, 2008); and (ii) statistical downscaling (SD), where statistical relationships between local climatic variables and GCM variables are used (Do Hoai et al., 2011; Pour et al., 2014; Wilby et al., 2004). Compared to dynamical downscaling, statistical downscaling methods are often preferred for their simplicity, easiness, flexibility, quickness and ability to provide local-scale information (Ahmed et al., 2015; Pour et al., 2014). The statistical downscaling methods are subdivided into two large groups, perfect prognosis (PP) and model output statistics (MOS) (Maraun et al., 2010). In PP, a statistical relationship is established between observed climate variables (predictand) and observed large-scale predictors while in MOS, the GCM simulated predictors instead of observed predictors are used to establish statistical relationship with observed predictands (Eden and Widmann, 2013). The MOS models are able to explicitly account for GCM-inherent error and bias (Eden and Widmann, 2013; Turco et al., 2011) and therefore, found highly potential for climate change simulations (Eden and Widmann, 2013; Sa'adi et al., 2017; Shirvani and Landman, 2015; Sunyer et al., 2015; Turco et al., 2017; Widmann et al., 2003). A number of methods are available for correction of bias in GCMs. However, the quantile mapping (QM) method is widely used as it has the capability to correct systematic distributional biases present in GCMs (Argüeso et al., 2013; Cannon et al., 2015; Teutschbein and Seibert, 2013; Themeßl et al., 2012).

The objective of the study was to investigate the impacts of climate change on groundwater level and irrigation cost for different RCP scenarios. A climate downscaling model based on model output statistics (MOS), an empirical hydrological model based on support vector machine (SVM) and an econometric model based on multiple-linear regression (MLR) were integrated in this study for this purpose. The proposed modeling framework was applied to assess the impacts on climate change induced changes in groundwater and irrigation cost in Rajshahi district located in Northwest Bangladesh (Fig. 1), where groundwater is the only source of irrigation during dry season. Declination of the groundwater level is a major concern in the area in recent years. The methodology provided in this study can be used to assess the impact of climate change on irrigation cost of groundwater-dependent irrigated crop with associated uncertainties for any climatic and geographic region. The knowledge generated through the application of proposed methodological framework can be used for planning adaptation to climate change impacts on livelihoods and economy of vast rural population of developing countries depending on groundwater-based irrigate agriculture.

2. Materials and methods

2.1. Data and sources

The monthly rainfall and temperature simulated by eight GCMs (Table 1) for historical (1961–2005) and future (2010–2099) periods were used in this study. The choice of the selection of GCMs was based on the availability of projections for all the three RCP scenarios for Bangladesh. The long-term daily rainfall and temperature record (1961–2005) from a meteorological station located in the Rajshahi District (within the study area) were collected from the Bangladesh Meteorological Department (BMD). The bi-monthly data of groundwater level (the depth to groundwater table from the land surface) recorded at 10 observation wells across the study area (Fig. 1) during 1991–2009 were obtained from the Bangladesh Water Development Board (BWDB), while the irrigation cost, irrigated area, groundwater withdrawal, groundwater-well age and harvesting date were collected from the BRAC (Bangladesh Rural Advancement Committee) Research Centre.

2.2. Methods

The methodology adopted in the present study is shown by the flowchart in Fig. 2. The climate downscaling, hydrological and irrigation cost models were integrated to assess the impacts of climate change induced changes in groundwater level and consequent changes in irrigation cost. A MOS downscaling technique was used for the downscaling of GCM simulated rainfall and temperature. An empirical model was developed using SVM for the simulation of groundwater depth from surface using climate and other influencing factors. A MLR model was developed to predict irrigation cost from groundwater level and other factors. The empirical groundwater model was calibrated and validated using historical observed data. The projected rainfall and temperature by downscaling models were then used in the model to simulate groundwater levels for three RCP scenarios. Finally, the projected groundwater level data were used in calibrated MLR model to forecast the impacts of climate change on irrigation cost. The irrigation costs were computed for all the GCMs under three RCP scenarios. Finally, the mean and the 95% confidence intervals of irrigation cost were calculated to show the changes in irrigation cost with uncertainty for each RCP scenarios. A description of the methods used in the study is given in the following sections.

2.3. Climate downscaling and projections

The procedure used for statistical downscaling of rainfall and temperature was consisted of three steps as outlined below:

1 The GCM simulated rainfall and temperature at four GCM grid points surrounding the study area were used to interpolate the rainfall and temperature at the point of meteorological station within the study area.
2 The QM bias correction approach was used to correct the biases in GCM simulated rainfall (temperature) by comparing the simulated rainfall (temperature) with observed rainfall (temperature) for the period 1961–2005.
3 The estimated QM parameters to correct biases in historical rainfall (temperature) were used for correcting the biases in GCM simulations for period 2010–2099.

The QM is a non-parametric bias correction approach. The adjustment of data using QM can be represented as empirical cumulative density function (CDF) and its inverse as below (Fang et al., 2015),

$$P_{cor,m} = ecdf_{obs,m}^{-1}(ecdf_{raw,m}(P_{raw,m})) \tag{1}$$

Where, $P_{cor,m}$ is the bias corrected rainfall of m-th month; $P_{raw,m}$ is rainfall of m-th month before bias correction; $ecdf_{obs,m}$ is the empirical CDF of observed data of m-th month; and $ecdf_{raw,m}$ is the CDF of rainfall of m-th month before bias correction. Description of the QM and its application to correct biases in the GCMs can be found in Fang et al., (2015). In the present study, QM bias correction approach was used to correct the biases in each GCM simulated rainfall or temperature separately.

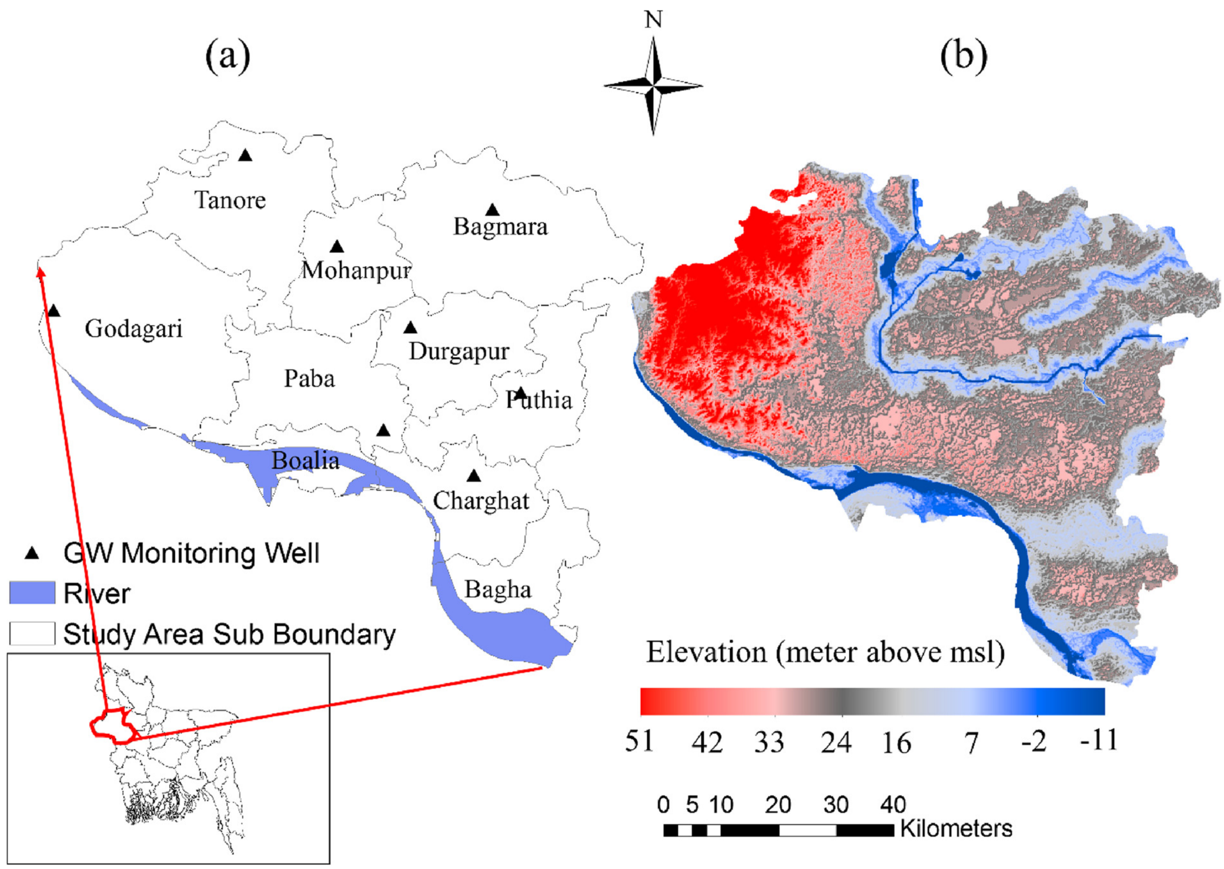

Fig. 1. (a) Location of the study area in the map of Bangladesh and the location of groundwater sampling points in the study area; (b) the topographic map of the study area.

2.4. Groundwater model

The physical factors that influence the groundwater level in the study area are considered for the selection of controlling factors of groundwater level fluctuation. Groundwater level in the study depends on the seasonal pattern of climate, irrigation abstraction, recharge from water bodies, etc. (Salem et al., 2017a). Four factors were considered in this study for modeling groundwater level through a thorough evaluation of all the natural and anthropogenic phenomena that may affect groundwater level in the area namely, the monthly total rainfall, crop evapotranspiration (ET), groundwater abstraction and irrigation return period from the paddy field. Rainfall and temperature are directly related to groundwater recharge while abstraction of groundwater to meet irrigation demand and irrigation return flow to aquifer directly affect groundwater level. Therefore, these four factors have been found capable of simulate groundwater level fluctuation in groundwater dependent irrigation region (Salem et al., 2017a, 2017b). The following steps were used to assess the impacts of climate change on groundwater level and the irrigation cost.

1 A water balance model (FAO-56) was used for the estimation of irrigation water demand or the groundwater abstraction. Groundwater abstraction was considered equal to irrigation demand as total water required for irrigation in dry season rice field in the study area comes from groundwater.
2 An SVM model was developed to simulate the depth to groundwater level from rainfall, evapotranspiration (ET), groundwater extraction and irrigation return flow data. The model was calibrated and validated with observed data for the period 1991 to 2009.
3 Irrigation demand under future climate change scenarios was estimated using a FAO-56 model which was considered as groundwater abstraction under climate change scenarios

Table 1
A list of the CMIP5 GCMs used in the present study.

No	Modeling Center	Model	Resolution (Longitude × Latitude)
1	Beijing Climate Center, China	BCC-CSM1-1	2.8°× 2.8°
2	Canadian Centre for Climate Modelling and Analysis, Canada	CanESM2	2.8°× 2.8°
3	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC5	1.4° × 1.4°
4	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC-ESM	2.8° × 2.8°
5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC-ESM-CHEM	2.8° × 2.8°
6	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute, Norway	NorESM1-M	2.5° × 1.9°
7	Max Planck Institute for Meteorology, Germany	MPI-ESM-LR	. 1.87°× 1.86°
8	Max Planck Institute for Meteorology, Germany	MPI-ESM-MR	1.87°× 1.86°

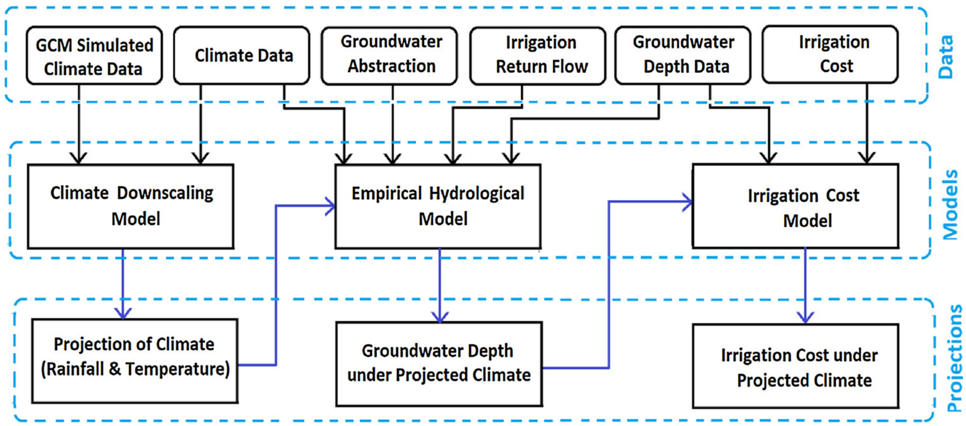

Fig. 2. The methodology adopted in the present study to assess climate change impacts on the groundwater level and irrigation cost.

4 The projected rainfall, ET under rising temperatures, groundwater abstraction due to climate change (estimated in step 3) and irrigation return flow for altered irrigation amount for the future period were used in the SVM model to estimate the future changes in groundwater level due to climate change.
5 The projected groundwater depths by different GCMs were used to estimate the mean change in groundwater depth and its 95% confidence interval using a Bayesian method for each RCP scenario.

2.5. Estimation of irrigation water demand

Various ET based models such as Priestley–Taylor, Penman, Hargreaves and Samini, Penman–Monteith, FAO-56, etc. have been proposed for estimation of irrigation water demand (Tukimat et al., 2012). These models employ different approaches for various aspects of crop water use and provide a wide range of estimation (Weiß and Menzel, 2008). A number of studies reported that FAO-56 method gives the best agreement with measured crop water use by lysimeter experiments when applied across environments (Kingston et al., 2009; Temesgen et al., 2005; Weiß and Menzel, 2008). FAO-56 incorporates the biological and physical processes involved in ET from cropped surfaces by relating ET to a specific crop and therefore, able to estimate the irrigation water requirement more accurately (Allen et al., 1998). Therefore, the FAO-56 model was used in this study to estimate the irrigation water demand,

$$W_{irr} = ET_{crop} + W_{lp} + W_{ps} + W_l - P_e \tag{2}$$

Where W_{irr} is irrigation water requirements; ET_{crop} is crop evapotranspiration; W_{lp} is water required for land preparation; W_{ps} is percolation and seepage losses of water from paddy field; W_l is water to establish standing water layer, and P_e is effective precipitation.

Accurate estimation of irrigation water demand depends on the reliable estimation of ET_{crop}, W_{ps} and P_e. Therefore, well-established methods in term of more accurate estimation of those parameters were used in this study. The Modified Penman method (Doorenbos and Pruitt, 1977) was used to compute the reference crop ET, and the crop coefficient values provided by FAO (Allen et al., 1998) were used to estimate ET_{crop}.The monthly effective precipitation was calculated using the method proposed by the United States Agriculture Department (United States et al., 1970). The percolation loss from the irrigation field was considered as the irrigation return flow from the rice field. Percolation loss through a particular soil class were calculated according to the percentage of sand, clay and loam in that soil class by following Brouwer and Heibloem, (1985). Because irrigation in the study area is mainly conducted from January to April, a bi-monthly time series of the irrigation return flow was constructed for only the irrigation period. The irrigation return flow in the other months was considered zero.

Total water required for irrigation in dry season rice field in the study area comes from groundwater (Ahammed et al., 2018). Therefore, groundwater abstraction was considered equal to irrigation demand in the present study. Estimated values of irrigation water demand, ET and effective precipitation were compared with that obtained in previous studies to show accuracy in estimation.

2.6. Estimation of uncertainty in groundwater level

Bayesian statistics was used to estimate the credible interval in the domain of the distribution of model output. Contrast to frequentist confidence interval, Bayesian interval estimation considers related information from the prior distribution whereas confidence intervals are based only on the data rather than a large number of repeated samples. For a given posterior, $P^{/}(M|R)$, the confidence interval for M $[M_{lo}, M_{hi}]$ is estimated using Bayesian approach as,

$$CI = \int_{M_{lo}}^{M_{hi}} P^{/}(M|R)dM \tag{3}$$

where, CI is the confidence interval; M_{hi} and M_{lo} are the upper and lower bounds of confidence intervals; M is model parameters; R is model output; the function P(M) is the set of different probabilities for variable M; $P^{/}(M|R)$ is the inverse probability distribution of R for given M; and dM represents normalization scale.

2.7. Irrigation cost model

The irrigation cost in groundwater-dependent irrigated region mainly depends on irrigated area and groundwater depth. Besides that, some other factors are also found to have influence on irrigation cost such as irrigation well efficiency, harvesting data, type of fuel used, etc. Greater advantage of rainfall can be taken by rescheduling the cropping period and therefore, the irrigation cost. The irrigation cost can also be reduced by improving well efficiency and electricity operated pumps. However, the diesel operated irrigation pumps are almost the sole pump-type is the study area due to lack of undisrupted power supply. Therefore, it is not considered as variable to derive irrigation cost model. Due to lack of availability of well-efficiency data, well age was considered as the proxy of well efficiency. The associations between irrigation cost and different factors were assessed to identify the influencing factors. Significant correlations between irrigation cost and irrigated area, groundwater level, and harvesting date were observed. No association was found between irrigation cost and well age and therefore, it was also not included for the development of irrigation cost model.

Besides being highly correlated with the output, the variables may also be correlated with each other, and the multicollinearity in input

variables can increase the likelihood of biased prediction. Therefore, the correlation among irrigated area, groundwater level, and harvesting date also estimate. As all the input variables define different physical property or phenomena, no significant correlation among them was observed. Therefore, these three variables were used to estimate the irrigation cost in the study area. A multiple linear regression (MLR) model was developed for this purpose. The MLR model relates the irrigation cost with the irrigated area, groundwater depth, and harvesting date. The obtained model is given below:

$$\text{Irrigation cost } (\times 10^3 \text{ BDT}) = 10.61 - 0.1 \times \text{Harvesting Date} + 1.13 \times \text{Irrigation Area} + 0.27 \times \text{Groundwater Depth} \quad (4)$$

The MLR model was used to assess how the irrigation cost varies with groundwater depth.

3. Results

3.1. Climate downscaling

Separate MOS model was developed for downscaling rainfall and temperature of each GCM. Observed and downscaled rainfall (temperature) data were compared to assess the reliability of MOS models to project future climate. The monthly observed and downscaled rainfall at the Rajshahi Station for GCM MIROC-ESM-CHEM is shown in Fig. 3 as an example. The result showed similarity between observed and downscaled rainfall. Similar results were obtained for other GCMs. However, it should be noted that GCMs are not developed for year to year forecasting of climate rather it is developed for long-term projection of climate and therefore, it cannot be expected that GCM simulated rainfall and temperature for historical period will accurately match with observed rainfall and temperature (Sa'adi et al., 2017). Therefore, the mismatch between observed and downscaled rainfall in some years as noticed in Fig. 3 may always happen. The performance of downscaling model was also assessed using statistical indices, namely, Nash-Sutcliff efficiency (NSE), correlation coefficient (R^2), mean absolute error (MAE) and root mean square error (RMSE). The results obtained for downscaling rainfall and temperature are shown in Figs. 4 and 5, respectively. The results revealed that the errors in the downscaled rainfall and temperature were less for all the GCMs. The NSE and R^2 values were more than 0.74 and 0.9, respectively, for all of the GCMs. This indicates that the MOS models were able to downscale rainfall and temperature in the study area efficiently and therefore can be used for the downscaling of GCM projected climate.

3.2. Climate projections

The mean of the projected rainfall and maximum temperature of eight GCMs under different RCP scenarios are shown in Fig. 6. The

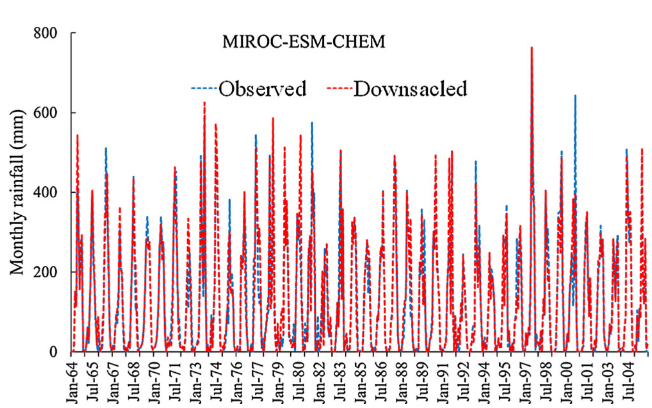

Fig. 3. A comparison of the monthly observed and downscaled rainfall of GCMs MIROC-ESM-CHEM at the Rajshahi Station.

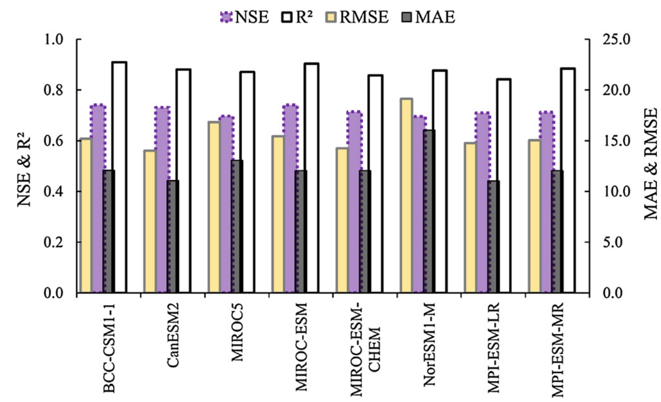

Fig. 4. Validation of the MOS models in downscaling rainfall using NSE (Nash-Sutcliff efficiency), R^2 (correlation coefficient), MAE (mean absolute error), and RMSE (root mean square error).

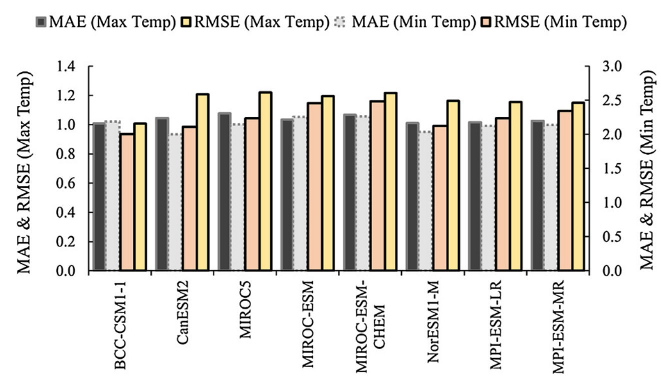

Fig. 5. Validation of the MOS models in the downscaling temperature using MAE (mean absolute error) and RMSE (root mean square error).

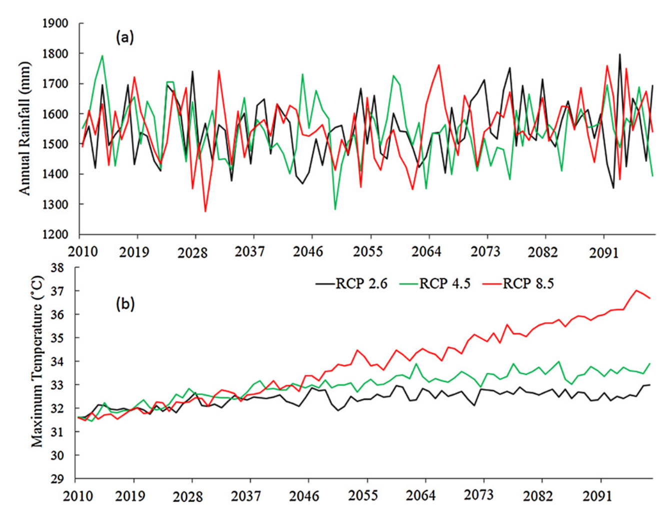

Fig. 6. The ensemble means of the projected (a) rainfall and (b) maximum temperature for different RCP scenarios in the study area.

results show that both the rainfall and maximum temperature will increase in the study area due to climate change. Changes in rainfall and temperature for all the GCMs for different RCPs are shown in Fig. 7. The average temperatures in northwest Bangladesh will increase in the range of 0.79 °C–3.74 °C at the end of this century. In general, the future projected temperature trend showed a good relationship with the degree of greenhouse gas emissions. The ensemble mean of the GCMs showed 1.33 °C, 1.76 °C and 2.33 °C increase in temperature for the low (RCP 2.6), medium (RCP 4.5) and high (RCP 8.5) emission scenarios,

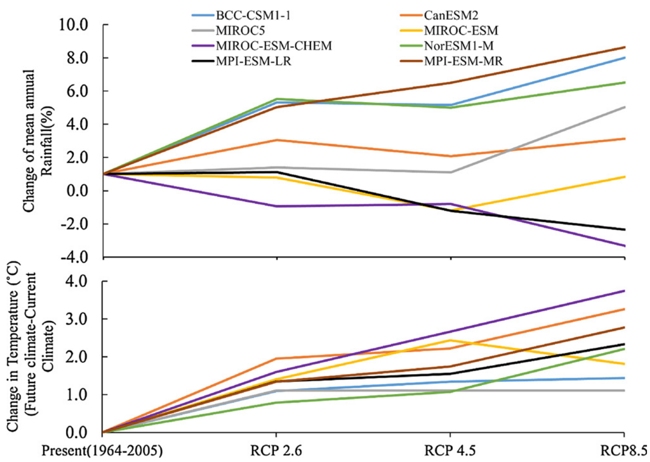

Fig. 7. Changes in rainfall (%) and temperature (°C) in the study area during 2070–2099 under different RCP scenarios.

respectively. However, changes in rainfall were not found as prominent as temperature. Rainfall was found to change in the range of −3.31% to 8.63% in the study area. The RCP 2.6 projected the lowest increase, while the RCP 8.5 projected the highest increase in rainfall. When analyzed for different future periods, a slight decrease in mean annual rainfall was found in the middle of the century 2040–2069 and then an increase in the last part of the century 2070–2099 for all the scenarios. The rainfall was also found to be more variable for RCP8.5 compared to RCP2.6 and RCP4.5. Rising temperature is likely to affect evapotranspiration and atmospheric water storage, and thereby the rainfall. Though the relationship between temperature and rainfall is non-linear, it has been reported that increase in temperature would cause an increase in rainfall in most part of the World (Shahid et al., 2016; Wang et al., 2016). Therefore, higher increase in rainfall has been projected for RCP8.5 scenario compared to other scenarios. The present study also found an increase in rainfall for RCP8.5.

3.3. Estimation of irrigation demand

Irrigation water demand at different locations in the study area was estimated using Eq (2). The crop evapotranspiration in the study area was found in the range of 340 to 461 mm, effective precipitation between 8.9 and 127.2 mm, the seepage and percolation losses in the range of 386 to 714 mm and the total irrigation demand between 981 and 1175 mm. Shahid, (2011) estimated irrigation water demand in the study area using same model and found that crop evapotranspiration in Northwest Bangladesh varies between 423 and 483 mm, effective precipitation between 37.6 and 81.6 mm, the seepage and percolation losses between 280 and 669 mm and the total irrigation demand of dry season *Borro* rice is between 839 and 1210 mm. Hossain et al., (2017) estimated crop evapotranspiration from a rice field in the range of 473 to 458 mm and seasonal irrigation water requirement of 1212 mm for dry season rice cultivation in the western part of Bangladesh. Irrigation water demand estimated in the present study collaborate well with that found in previous studies and therefore, it can be remarked that the evapotranspiration, effective precipitation and irrigation water demand or groundwater abstraction estimated in this study is reliable.

3.4. Modeling the groundwater level

Separate SVM model was developed for each groundwater monitoring well. The SVM models were calibrated and validated with 70% and 30% of the observed groundwater depth data respectively. The observed and predicted depths to groundwater level matched very well during both model calibration and validation. The performance of the models during calibration and validation at three locations is summarized in Table 2. The RMSE values were found very low (0.84–2.12), and R^2 and NSE values greater than 0.59 in all of the cases.

Table 2
Root mean square error (RMSE), correlation coefficient (R^2) and the Nash-Sutcliff efficiency (NSE) during SVM model calibration and validation at a few selected stations.

Station Name	Calibration			Validation		
	RMSE	NSE	R^2	RMSE	NSE	R^2
Charghat	1.023	0.599	0.775	0.971	0.664	0.827
Durgapure	1.694	0.663	0.823	1.708	0.632	0.815
Bagmara	2.054	0.833	0.914	1.794	0.826	0.917

3.5. Change in groundwater depth under the projected climate

The calibrated and validated SVM models were used to project future changes in groundwater depth under the projected climate. For this purpose, the projected rainfall and ET (estimated from the projected temperature) by different GCMs were used as inputs into the models. The irrigation water demand under projected climate was estimated to proxy the groundwater abstraction. The percolation losses of irrigation water for different GCM simulated climate were also estimated and used as input into the SVM models. Different GCMs projected different groundwater depths for the study area. The mean of the projected groundwater depth under different RCP scenarios obtained at different locations were interpolated to prepare the map of the groundwater depth under the projected climate. The spatial distribution of the projected groundwater depth for three future periods under different scenarios is shown in Fig. 8. The figure shows that the groundwater level will decrease more in the western and northeast parts of the study area. The maximum declination of the groundwater level will be during 2070–2099 for RCP 8.5. The GCM MIROC-ESM-CHEM projected the highest decrease in groundwater level in the northeast part of the study area in the range of 2.23–4.12 m, while the GCM MPI-ESM-LR projected the least decrease (0.05 – 0.1) m in the central part.

Sensitivity of groundwater level to rainfall and temperature was assessed by varying rainfall and ET separately, while all other parameters were kept constant. It was observed that a 1% increase in ET in the reference period (1991–2009) caused a decrease in groundwater depth by 1.6% during the irrigation period. On the other hand, a 1%

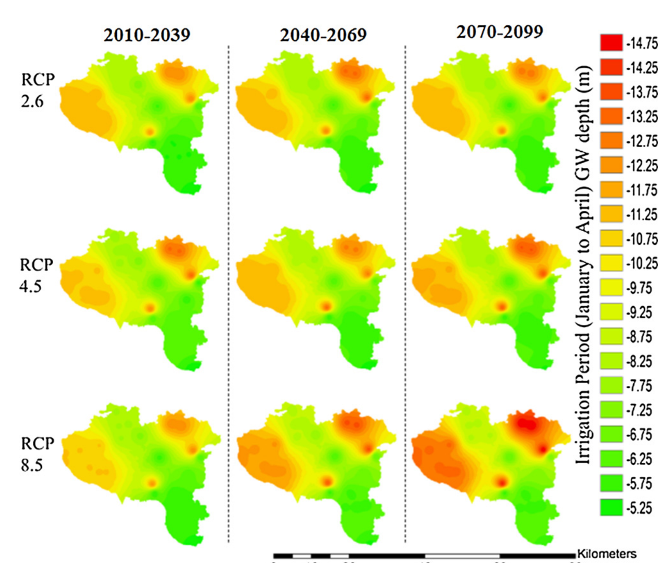

Fig. 8. Projected groundwater depth during irrigation season (January to April) for three future periods namely, 2010–2039, 2040–2069, and 2070–2099 under three RCP scenarios.

increase in rainfall for the same reference period showed an increase in the groundwater table by 0.2%.

Rainfall during irrigation period mainly occurs only March and April as thunderstorm. The short and intense rainfall produces much runoff compared to groundwater recharge. Therefore, increase in pre-monsoon rainfall does not affect groundwater recharge much. On the other hand, temperature during March and April is higher compared to other months which cause higher ET from paddy field (Mohsenipour et al., 2018). The higher ET decreases soil moisture as well as groundwater recharge and groundwater level. Therefore, groundwater level in the study area is more sensible to temperature compared to rainfall during irrigated crop growing season. The higher declination of groundwater table for RCP8.5 might be due to the higher increase of temperature for this scenario compared to other scenarios.

3.6. Uncertainty in the projected groundwater depth

The groundwater depths projected by different GCMs were used to estimate the uncertainty in the groundwater depth using Bayesian method. The upper and lower bounds of 95% confidence interval band along with the mean of the projected groundwater levels for the different future periods under three RCP scenarios at two out of ten locations are presented in Fig. 9 as an example. The RCP2.6 and RCP4.5 are low and intermediate emission scenarios. The RCP 2.6 scenario considers that CO_2 concentrations peak around 2050 followed by a modest decline by 2099, while RCP 4.5 considers slight increase in CO_2 emissions before decline commences around 2040. The temperatures in the study area were found to become stable in last part of the century for these two scenarios. Therefore, groundwater level was found to decrease until 2069 followed by a slight increase in the end of the century. On the other hand, both the maximum and minimum temperatures in the study area were found to increase continuously over the century and therefore, the declination of groundwater level under RCP 8.5 scenario. However, as the relationship between climate and groundwater level is not linear, it is not possible to explain all the changes in groundwater levels through simple analysis of rainfall and temperature.

The range between the upper and lower bounds of groundwater depth provided uncertainty in the projected groundwater level. It was found that there was more uncertainty in the groundwater level for RCP 8.5 compared to other scenarios. The uncertainty band in areal average groundwater level was found in the range of 0.98 to 0.74 m for RCP 2.6, 1.23 to 0.97 m for RCP 4.5, and 1.77 to 0.74 m for RCP 8.5. The upper bound to the uncertainty was wider compared to the lower bound for all of the RCPs. This indicates that the projections of a higher declination of groundwater level are more uncertain.

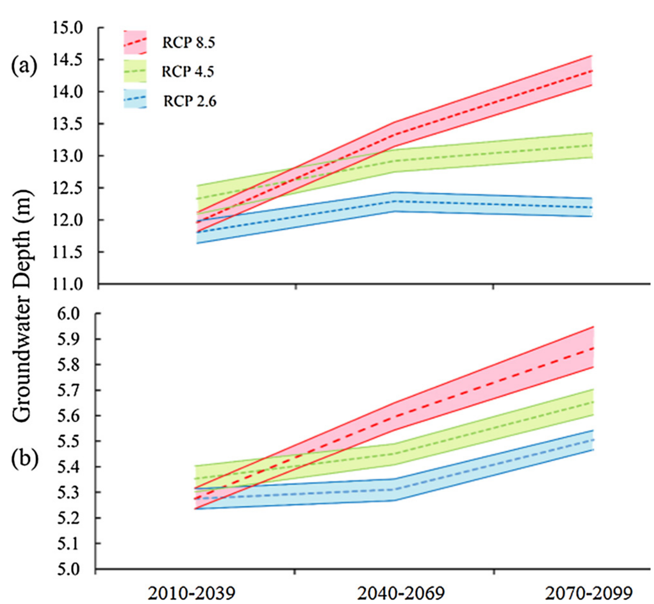

Fig. 9. The mean and 95% confidence interval of the groundwater depth at two locations (Fig. 1) in the study area: (a) Poba and (b) Bagha under three RCP scenarios.

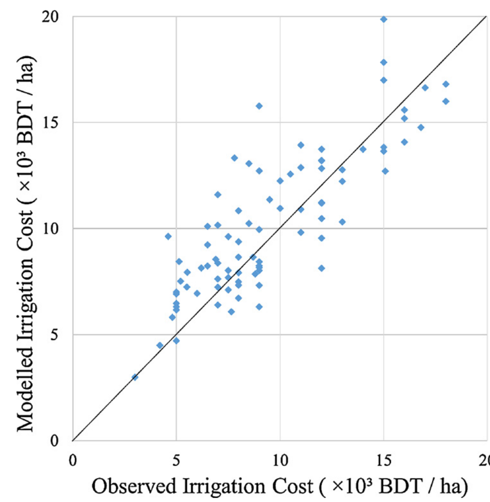

Fig. 10. The scatter plot showing the relationship between the observed and simulated irrigation cost.

3.7. Impacts of groundwater depth on irrigation cost

The irrigation cost model (Eq. (4)) was verified through the scatter plot of the observed and the simulated irrigation cost shown in Fig. 10. The figure shows that most of the points are aligned along the diagonal line, which indicates that the model can be used to forecast irrigation cost with reasonable accuracy. The correlation coefficient between the observed and modeled irrigation cost was 0.72, which also indicates the reliability of the model.

3.8. Irrigation cost under projected climate

The MLR model was used to project the future changes in irrigation cost due to climate change induced declination of the groundwater level. The uncertainty in the irrigation cost due to uncertainty in the groundwater level drop under different climate change scenarios were also assessed. The obtained results are presented in Fig. 11. The results show an increase in average irrigation cost due to groundwater level drop, which was in the range of 0.12 to 0.32 thousand BDT (1.61–4.30 USD) per ha, 0.15 to 0.48 thousand BDT (2.01–6.45 USD) per ha and 0.21 to 0.73 thousand BDT (2.82–9.82 USD) per ha for RCP 2.6, RCP 4.5 and RCP 8.5 scenarios, respectively. The result revealed that the minimum increase of the irrigation cost will be 0.12 thousand BDT (1.61 USD) per ha and the maximum will be 0.73 thousand BDT (9.82

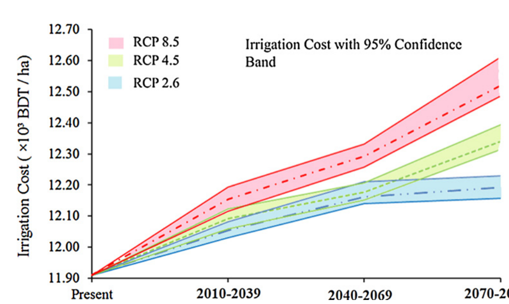

Fig. 11. The increase in the irrigation cost with the 95% confidence interval due to declination of the groundwater level under three RCP scenarios.

USD) per ha due to climate change. The maximum increase in irrigation cost was projected by GCM MIROC-ESM-CHEM in the northeast part of the study area in the range of 0.6–1.1 thousand BDT (8.07–14.79 USD) per ha, while the least increase in irrigation cost was projected in the central part of the study area by GCM MPI-ESM-LR in the range of 0.01 to 0.04 thousand BDT (0.13 to 0.53 USD) per ha.

4. Discussion

In the present study, MOS models were developed for downscaling of GCM simulated rainfall and temperature for the study area. The systematic distributional biases present in GCM climate outputs were corrected in respect to observed climate using the QM method. The comparison of observed and downscaled data proved that the MOS models were able to downscale the climate of the study area. Therefore, the projections of the GCMs downscaled by the models can be trusted for the impact assessment.

The projections of climate in northwest Bangladesh revealed a sharp rise in temperature but a small change in rainfall. The findings of the study matched well with the recent climate trends in the study area (Shahid, 2011) and future climate projected by others (Islam et al., 2008; Rahman et al., 2012; Rajib et al., 2011). A significant increase in temperature and no appreciable change in rainfall, except during the monsoon season, may cause further declination of groundwater level during the irrigation period.

Numerous conceptual and process-based models have been developed and successfully applied for simulating groundwater level in a variety of hydrogeological settings (Coppola et al., 2005; Gholami et al., 2015; Uddameri, 2007). However, the physically based models are highly data-intensive, labour-intensive and expensive, which often hinder the development of such models in data-scarce regions (Nikolos et al., 2008). Recent studies have reported the impressive predictive accuracy of empirical models based on machine learning methods in groundwater level simulation (Sahoo et al., 2017; Shortridge et al., 2016). Among the machine learning methods, SVM is found to perform better in groundwater level simulations because of its capability to simulate highly non-linear relationships (Behzad Mohsen et al., 2010; Ch and Mathur, 2012; Guzmán et al., 2018; Raghavendra and Deka, 2015; Salem et al., 2017b; Sudheer et al., 2014; Tapak et al., 2014; Yoon et al., 2016). The present study showed that SVM was able to precisely predict historical groundwater levels, which proves the capability of SVM to simulate groundwater depth under the projected climate. The SVM models estimated a decrease in groundwater level under all climate change scenarios. The minimum declination of the areal average of groundwater level was projected in the range of 0.45 m to 2.71 m. Insufficient recharge due to an increase in ET under elevated temperature, but no significant increase in precipitation during the irrigation months, may be the reason for the groundwater level drop in northwest Bangladesh. The present study also revealed that four factors namely, the monthly total rainfall, crop evapotranspiration (ET), groundwater abstraction and irrigation return flow from the paddy field are capable of modeling groundwater level fluctuation in the study area reliably.

The study estimated increases in average irrigation cost in the study area in the range of 0.12 to 0.73 thousand BDT (1.61–9.82 USD) per ha at the 95% confidence interval due to climate change. Irrigation shares 21.81% of the total cost of paddy production in northwest Bangladesh, whereas labor cost is the highest (37.01%), and the rest is for fertilizer (14.44%) and other associated costs (Basak, 2011). Therefore, labor, irrigation and chemical costs define the price of rice or the farmers' benefits in Bangladesh. Diesel for operating pumps is becoming a major agricultural input in Bangladesh with the expansion of groundwater based irrigated cultivation (Haque et al., 2013). Therefore, the irrigation cost in Bangladesh mainly depends on fuel price. This study revealed that the irrigation cost in Bangladesh will not only fluctuate due to the increasing cost of fuel or electricity, but it will also increase due to climate change induced declination of groundwater level.

An analysis of the agricultural labor wage data for 2001–2010 revealed that the agricultural labor cost in Bangladesh increased at a rate of 9.9% per year (Department of Agricultural Marketing Bangladesh, 2016). The fertilizer and pesticide price was found to highly fluctuate; however, there was an average increase of chemical cost by 1.8% per year. It has been reported that soil fertility in Bangladesh has decreased in recent years, and more fertilizer are required to maintain crop production (Shahid et al., 2006). Furthermore, a large amount of fertilizer is being used to cultivate high yielding varieties, and consequently, the demand for chemical fertilizers is following an increasing trend. Therefore, it is very clear that fertilizer cost combined with labor cost will be a major driving force for the increase in crop production cost in Bangladesh. Basak, (2011) and Miah et al., (2008) also noted that the major component of rice production costs in Bangladesh will be due to labor and chemical costs. In addition, an increasing trend in fuel price has been noticed in Bangladesh like other parts of the world. Though fuel price fluctuates according to international price and the government policy of fuel subsidies, the long-term trend indicates a clear increase in fuel price in Bangladesh. Increases in fuel cost will certainly cause an increase in irrigation costs in Bangladesh along with labor and chemical costs. The present study revealed that the irrigation cost in Bangladesh will also increase due to the declination of groundwater level caused by climate change. However, the study revealed a large declination of groundwater level at the locations where the depth to groundwater level is already very high. It indicates that increase in irrigation cost due to climate change will be significant in the locations where the depth to groundwater level is already very high and groundwater level is declining very fast.

5. Conclusions

The impacts of climate change on groundwater dependent irrigation cost in northwest Bangladesh was assessed in the study using an ensemble of eight GCMs of CMIP5 for three RCP scenarios. The results show that climate change will cause an increase in both annual mean of daily temperature and total rainfall in the study area. However, a comparatively higher increase in temperature and no appreciable change in rainfall in winter and pre–monsoon months will cause further declination of groundwater levels during the pre-monsoon irrigation period. The study reveals that the declination of groundwater level due to climate change will increase the irrigation cost for all of three RCP scenarios. However, the amount of groundwater declination and consequent increase in the irrigation cost will depend on climate change scenarios. The study projects the maximum declination of average groundwater level by 1.19, 1.79 and 2.71 for RCP 2.6, RCP 4.5 and RCP 8.5 scenarios respectively, which will cause an increase in average irrigation cost by 0.32, 0.48 and 0.73 thousand BDT (4.3, 6.45 and 9.82 USD) respectively. Analysis of data reveals that the increases in irrigation cost due to a climate change-induced groundwater level drop is much less compared to that for the increases in labor charge, fuel prices and fertilizer costs. However, it may be significant in the regions where the depth to groundwater level is high.

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References

Ahammed, S.J., Chung, E.-S., Shahid, S., 2018. Parametric assessment of pre-monsoon agricultural water scarcity in Bangladesh. Sustainability 10, 819.

Ahmed, K., Shahid, S., Haroon, S.B., Xiao-jun, W., 2015. Multilayer perceptron neural network for downscaling rainfall in arid region: a case study of Baluchistan, Pakistan. J. Earth Syst. Sci. 124, 1325–1341. http://dx.doi.org/10.1007/s12040-015-0602-9.
Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56. FAO, Rome 300, D05109.
Argüeso, D., Evans, J.P., Fita, L., 2013. Precipitation bias correction of very high resolution regional climate models. Hydrol. Earth Syst. Sci. 17, 4379–4388. http://dx.doi.org/10.5194/hess-17-4379-2013.
Basak, J.K., 2011. Impacts of Increasing Production Costs on Rice Price: Implications for Food Security. Unnayan Onneshan, Dhaka.
Behzad Mohsen, Asghari, Keyvan, Coppola, Emery, A., 2010. Comparative study of SVMs and ANNs in aquifer Water level prediction. J. Comput. Civil Eng. 24, 408–413. http://dx.doi.org/10.1061/(ASCE)CP.1943-5487.0000043.
Brouwer, C., Heibloem, M., 1985. Irrigation Water Management: Training Manual No. 3: Irrigation Water Needs. Food and Agriculture Organization of the United Nations, Rome, Italy.
Cannon, A.J., Sobie, S.R., Murdock, T.Q., 2015. Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? J. Clim. 28, 6938–6959. http://dx.doi.org/10.1175/JCLI-D-14-00754.1.
Ch, S., Mathur, S., 2012. Groundwater level forecasting using SVM-PSO. Int. J. Hydrol. Sci. Technol. 2, 202–218. http://dx.doi.org/10.1504/IJHST.2012.047432.
Coppola, E.A., Rana, A.J., Poulton, M.M., Szidarovszky, F., Uhl, V.W., 2005. A neural network model for predicting aquifer water level elevations. Ground Water 43, 231–241. http://dx.doi.org/10.1111/j.1745-6584.2005.0003.x.
Davidson, S., Yang, L., 2007. Impacts of Climate Variability and Changes on Groundwater Recharge in the Semi-Arid Southwestern United States.
Department of Agricultural Marketing Bangladesh, 2016. Annual Report of Department of Agricultural Marketing 2014-2015. Department of Agricultural Marketing (DAM), Ministry of Agricultural, Government of Bangladesh.
Do Hoai, N., Udo, K., Mano, A., 2011. Downscaling global weather forecast outputs using ANN for flood prediction. J. Appl. Math. http://dx.doi.org/10.1155/2011/246286.
Doorenbos, J., Pruitt, W.O., 1977. Guidelines for Predicting Crop Water Requirments. Irrigation and Drainage Paper 24: Crop Water Requirements. FAO, Roma, pp. 156.
Eden, J.M., Widmann, M., 2013. Downscaling of GCM-simulated precipitation using model output statistics. J. Clim. 27, 312–324. http://dx.doi.org/10.1175/JCLI-D-13-00063.1.
Fang, G.H., Yang, J., Chen, Y.N., Zammit, C., 2015. Comparing bias correction methods in downscaling meteorological variables for a hydrologic impact study in an arid area in China. Hydrol. Earth Syst. Sci. 19, 2547–2559. http://dx.doi.org/10.5194/hess-19-2547-2015.
Gandhi, V.P., Bhamoriya, V., 2011. Groundwater Irrigation in India. India infrastructure report 90. .
Gao, P., Carbone, G.J., Guo, D., 2016. Assessment of NARCCAP model in simulating rainfall extremes using a spatially constrained regionalization method. Int. J. Climatol. 36, 2368–2378. http://dx.doi.org/10.1002/joc.4500.
Garrote, L., Iglesias, A., Granados, A., Mediero, L., Martin-Carrasco, F., 2015. Quantitative assessment of climate change vulnerability of irrigation demands in Mediterranean Europe. Water Resour. Manag. 29, 325–338. http://dx.doi.org/10.1007/s11269-014-0736-6.
Gholami, V., Chau, K.W., Fadaee, F., Torkaman, J., Ghaffari, A., 2015. Modeling of groundwater level fluctuations using dendrochronology in alluvial aquifers. J. Hydrol. 529, 1060–1069. http://dx.doi.org/10.1016/j.jhydrol.2015.09.028.
Guzmán, S.M., Paz, J.O., Tagert, M.L.M., Mercer, A.E., Pote, J.W., 2018. An integrated SVR and crop model to estimate the impacts of irrigation on daily groundwater levels. Agric. Syst. 159, 248–259. http://dx.doi.org/10.1016/j.agsy.2017.01.017.
Haque, M.A., Islam, M.S., Zahid, A., 2013. Groundwater irrigation and crop economy in the lower gangetic plain at Matbarer Char, Madaripur, South-Central Bangladesh. J. Asiatic Soc. Bangladesh Sci. 38, 29–39. http://dx.doi.org/10.3329/jasbs.v38i1.15318.
Hossain, M.B., Yesmin, S., Maniruzzaman, M., Biswas, J.C., 2017. Irrigation scheduling of rice (Oryza sativa L.) Using CROPWAT model in the Western region of Bangladesh. Agriculturists 15, 19–27. http://dx.doi.org/10.3329/agric.v15i1.33425.
Islam, M.N., Rafiuddin, M., Ahmed, A.U., Kolli, R.K., 2008. Calibration of PRECIS in employing future scenarios in Bangladesh. Int. J. Climatol. 28, 617–628. http://dx.doi.org/10.1002/joc.1559.
Kingston, D.G., Todd, M.C., Taylor, R.G., Thompson, J.R., Arnell, N.W., 2009. Uncertainty in the estimation of potential evapotranspiration under climate change. Geophys. Res. Lett. 36. http://dx.doi.org/10.1029/2009GL040267.
Kovacs, K., West, G., 2016. The influence of groundwater depletion from irrigated agriculture on the tradeoffs between ecosystem services and economic returns. PLoS One 11, e0168681. http://dx.doi.org/10.1371/journal.pone.0168681.
Laprise, R., 2008. Regional climate modelling. J. Comput. Phys. 227, 3641–3666. http://dx.doi.org/10.1016/j.jcp.2006.10.024.
Maraun, D., Wetterhall, F., Ireson, A.M., Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W., Sauter, T., Themeßl, M., Venema, V.K.C., Chun, K.P., Goodess, C.M., Jones, R.G., Onof, C., Vrac, M., Thiele-Eich, I., 2010. Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user. Rev. Geophys. 48. http://dx.doi.org/10.1029/2009RG000314.
Medellín-Azuara, J., MacEwan, D., Howitt, R.E., Koruakos, G., Dogrul, E.C., Brush, C.F., Kadir, T.N., Harter, T., Melton, F., Lund, J.R., 2015. Hydro-economic analysis of groundwater pumping for irrigated agriculture in California's Central Valley, USA. Hydrogeol. J. 23, 1205–1216. http://dx.doi.org/10.1007/s10040-015-1283-9.
Miah, M.M., Saha, P.K., Islam, A., Hasan, M.N., Nosov, V., 2008. Potassium fertilization in rice-rice and rice-wheat cropping system in Bangladesh. Bangladesh J. Agric. Environ. 4, 51–67.
Mohsenipour, M., Shahid, S., Chung, E., Wang, X., 2018. Changing pattern of droughts during cropping seasons of Bangladesh. Water Resour. Manag. 32, 1555–1568. http://dx.doi.org/10.1007/s11269-017-1890-4.
Mulangu, F., Kraybill, D., 2015. A cost–benefit analysis of improved irrigation when faced with the risks of climate change on Mount Kilimanjaro. Water Resour. Econ. 10, 31–44. http://dx.doi.org/10.1016/j.wre.2015.01.001.
Narayanamoorthy, A., 2015. Groundwater depletion and water extraction cost: some evidence from South India. Int. J. Water Resour. Dev. 31, 604–617. http://dx.doi.org/10.1080/07900627.2014.935302.
Nayak, P.C., Wardlaw, R., Kharya, A.K., 2015. Water balance approach to study the effect of climate change on groundwater storage for Sirhind command area in India. Int. J. River Basin Manag. 13, 243–261. http://dx.doi.org/10.1080/15715124.2015.1012206.
Nelson, G.C., Rosegrant, M.W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Palazzo, A., Msangi, S., Batka, M., Magalhaes, M., Valmonte-Santos, R., Ewing, M., Lee, D., 2010. The Costs of Agricultural Adaptation to Climate Change (No. 56662). The World Bank.
Nikolos, I.K., Stergiadi, M., Papadopoulou, M.P., Karatzas, G.P., 2008. Artificial neural networks as an alternative approach to groundwater numerical modelling and environmental design. Hydrol. Process. 22, 3337–3348. http://dx.doi.org/10.1002/hyp.6916.
Pengra, B., 2012. A Glass Half Empty: Regions at Risk Due to Groundwater Depletion Why is This Issue Important? United Nations Environment Programme. https://na.unep.net/geas/getUNEPPageWithArticleIDScript.php?article_id=76.
Pour, S.H., Harun, S.B., Shahid, S., 2014. Genetic programming for the downscaling of extreme rainfall events on the East Coast of peninsular Malaysia. Atmosphere 5, 914–936. http://dx.doi.org/10.3390/atmos5040914.
Raghavendra, N.S., Deka, P.C., 2015. Forecasting monthly groundwater level fluctuations in coastal aquifers using hybrid wavelet packet–support vector regression. Cogent Eng. 2, 999414. http://dx.doi.org/10.1080/23311916.2014.999414.
Rahman, M.M., Islam, M.N., Ahmed, A.U., Georgi, F., 2012. Rainfall and temperature scenarios for Bangladesh for the middle of 21st century using RegCM. J. Earth Syst. Sci. 121, 287–295. http://dx.doi.org/10.1007/s12040-012-0159-9.
Rajib, M.A., Rahman, M.M., Islam, A., Saiful, A.K.M., McBean, E.A., 2011. Analyzing the Future Monthly Precipitation Pattern in Bangladesh from Multi-Model Projections Using Both GCM and RCM, ASCE World Environmental and Water Resources Congress 2011. http://dx.doi.org/10.1061/41173(414)402. Proceedings.
Ranjan, P., Kazama, S., Sawamoto, M., 2006. Effects of climate change on coastal fresh groundwater resources. Global Environmental Change 16, 388–399. http://dx.doi.org/10.1016/j.gloenvcha.2006.03.006.
Sa'adi, Z., Shahid, S., Chung, E.-S., Ismail, T.bin, 2017. Projection of spatial and temporal changes of rainfall in Sarawak of Borneo Island using statistical downscaling of CMIP5 models. Atmos. Res. 197, 446–460. http://dx.doi.org/10.1016/j.atmosres.2017.08.002.
Sahoo, S., Russo, T.A., Elliott, J., Foster, I., 2017. Machine learning algorithms for modeling groundwater level changes in agricultural regions of the U.S. Water Resour. Res. 53, 3878–3895. http://dx.doi.org/10.1002/2016WR019933.
Salem, G.S.A., Kazama, S., Komori, D., Shahid, S., Dey, N.C., 2017a. Optimum abstraction of groundwater for sustaining groundwater level and reducing irrigation cost. Water Resour. Manag. 31, 1947–1959. http://dx.doi.org/10.1007/s11269-017-1623-8.
Salem, G.S.A., Kazama, S., Shahid, S., Dey, N.C., 2017b. Impact of temperature changes on groundwater levels and irrigation costs in a groundwater-dependent agricultural region in Northwest Bangladesh. Hydrol. Res. Lett. 11, 85–91. http://dx.doi.org/10.3178/hrl.11.85.
Shahid, S., 2011. Impact of climate change on irrigation water demand of dry season *Boro* rice in northwest Bangladesh. Clim. Change 105, 433–453. http://dx.doi.org/10.1007/s10584-010-9895-5.
Shahid, S., Hazarika, M.K., 2010. Groundwater drought in the northwestern districts of Bangladesh. Water Resour. Manag. 24, 1989–2006. http://dx.doi.org/10.1007/s11269-009-9534-y.
Shahid, S., Chen, X., Hazarika, M., 2006. Evaluation of groundwater quality for irrigation in Bangladesh using geographic information system. J. Hydrol. Hydromech. 54.
Shahid, S., Wang, X.-J., Rahman, M.M., Hasan, R., Harun, S.B., Shamsudin, S., 2015. Spatial assessment of groundwater over-exploitation in northwestern districts of Bangladesh. J. Geol. Soc. India 85, 463–470. http://dx.doi.org/10.1007/s12594-015-0238-z.
Shahid, S., Wang, X.-J., Harun, S.B., Shamsudin, S.B., Ismail, T., Minhans, A., 2016. Climate variability and changes in the major cities of Bangladesh: observations, possible impacts and adaptation. Reg. Environ. Change 16, 459–471. http://dx.doi.org/10.1007/s10113-015-0757-6.
Shahid, S., Alamgir, M., Wang, X., Eslamian, S., 2017. Climate change impacts on and adaptation to groundwater. In: Eslamian, S., Eslamian, F. (Eds.), Handbook of Drought and Water Scarcity. CRC Press, Taylor & Francis Group, 6000 Broken Sound Parkway NW, Suite 300, Boca Raton, FL 33487-3742, pp. 107–123. http://dx.doi.org/10.1201/9781315226781-7.
Shirvani, A., Landman, W., 2015. Seasonal precipitation forecast skill over Iran. Int. J. Climatol. http://dx.doi.org/10.1002/joc.4467.
Shortridge, J.E., Guikema, S.D., Zaitchik, B.F., 2016. Machine learning methods for empirical streamflow simulation: a comparison of model accuracy, interpretability, and uncertainty in seasonal watersheds. Hydrol. Earth Syst. Sci. 20, 2611–2628. http://dx.doi.org/10.5194/hess-20-2611-2016.
Siebert, S., Burke, J., Faures, J.M., Frenken, K., Hoogeveen, J., Döll, P., Portmann, F.T., 2010. Groundwater use for irrigation – a global inventory. Hydrol. Earth Syst. Sci. 14, 1863–1880. http://dx.doi.org/10.5194/hess-14-1863-2010.
Srivastava, S., Chand, R., Singh, J., Kaur, A., Jain, R., Kingsly, I., Raju, S.S., 2017.

Revisiting groundwater depletion and its implications on farm economics in Punjab, India. Curr. Sci. India 113, 422–429. http://dx.doi.org/10.18520/cs/v113/i03/422-429.
Su, F., Zhang, L., Ou, T., Chen, D., Yao, T., Tong, K., Qi, Y., 2016. Hydrological response to future climate changes for the major upstream river basins in the Tibetan Plateau. Glob. Planet. Change 136, 82–95. http://dx.doi.org/10.1016/j.gloplacha.2015.10.012.
Sudheer, C., Maheswaran, R., Panigrahi, B.K., Mathur, S., 2014. A hybrid SVM-PSO model for forecasting monthly streamflow. Neural Comput. Appl. 24, 1381–1389. http://dx.doi.org/10.1007/s00521-013-1341-y.
Sunyer, M.A., Gregersen, I.B., Rosbjerg, D., Madsen, H., Luchner, J., Arnbjerg-Nielsen, K., 2015. Comparison of different statistical downscaling methods to estimate changes in hourly extreme precipitation using RCM projections from ENSEMBLES. Int. J. Climatol. 35, 2528–2539. http://dx.doi.org/10.1002/joc.4138.
Tapak, L., Rahmani, A.R., Moghimbeigi, A., 2014. Prediction the groundwater level of Hamadan-Bahar Plain, west of Iran using support vector machines. J. Res. Health Sci. 14, 81–86.
Temesgen, Bekele, Eching, Simon, Davidoff, Baryohay, Frame, Kent, 2005. Comparison of some reference evapotranspiration equations for California. J. Irrig. Drain. Eng. 131, 73–84. http://dx.doi.org/10.1061/(ASCE)0733-9437(2005)131:1(73).
Teutschbein, C., Seibert, J., 2013. Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions? Hydrol. Earth Syst. Sci. 17, 5061–5077. http://dx.doi.org/10.5194/hess-17-5061-2013.
Themeßl, M.J., Gobiet, A., Heinrich, G., 2012. Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. Clim. Change 112, 449–468. http://dx.doi.org/10.1007/s10584-011-0224-4.
Treidel, H., Martin-Bordes, J.J., Gurdak, J.J. (Eds.), 2012. Climate Change Effects on Groundwater Resources: a Global Synthesis of Findings and Recommendations, International Association of Hydrologists (IAH) - International Contributions to Hydrogeology. Taylor & Francis Publication 414 p.
Tukimat, N.N.A., Harun, S., Shahid, S., 2012. Comparison of different methods in estimating potential evapotranspiration at Muda Irrigation Scheme of Malaysia. J. Agric. Rural Dev. Trop. Subtropics (JARTS) 113, 77–85.
Turco, M., QuintanaSeguí, P., Llasat, M.C., Herrera, S., Gutiérrez, J.M., 2011. Testing MOS precipitation downscaling for ENSEMBLES regional climate models over Spain. J. Geophys. Res. Atmos. 116. http://dx.doi.org/10.1029/2011JD016166.
Turco, M., Llasat, M.C., Herrera, S., Gutiérrez, J.M., 2017. Bias correction and downscaling of future RCM precipitation projections using a MOS-analog technique. J. Geophys. Res.Atmos. 122, 2631–2648. http://dx.doi.org/10.1002/2016JD025724.
Uddameri, V., 2007. Using statistical and artificial neural network models to forecast potentiometric levels at a deep well in South Texas. Environ. Geol. 51, 885–895. http://dx.doi.org/10.1007/s00254-006-0452-5.
United States, Soil Conservation Service, Engineering Division, 1970. Irrigation Water Requirements /United States Department of Agriculture, Soil Conservation Service, Engineering Division. United States Department of Agriculture, Soil Conservation Service, Engineering Division.
Wang, X., Zhang, J., Ali, M., Shahid, S., He, R., Xia, X., Jiang, Z., 2016. Impact of climate change on regional irrigation water demand in Baojixia irrigation district of China. Mitigation Adapt. Strategies Glob. Change 21, 233–247. http://dx.doi.org/10.1007/s11027-014-9594-z.
Weiß, M., Menzel, L., 2008. A global comparison of four potential evapotranspiration equations and their relevance to stream flow modelling in semi-arid environments. Adv. Geosci. 18, 15–23. http://dx.doi.org/10.5194/adgeo-18-15-2008.
Widmann, M., Bretherton, C.S., Salathé, E.P., 2003. Statistical precipitation downscaling over the Northwestern United States using numerically simulated precipitation as a predictor. J. Clim. 16, 799–816. http://dx.doi.org/10.1175/1520-0442(2003)016<0799:SPDOTN>2.0.CO;2.
Wilby, R., Charles, S., Zorita, E., Timbal, B., Whetton, P., Mearns, L., 2004. Guidelines For Use of Climate Scenarios Developed From Statistical Downscaling Methods. Supporting Material of the Intergovernmental Penel on Climate Change.
Yoon, H., Hyun, Y., Ha, K., Lee, K.-K., Kim, G.-B., 2016. A method to improve the stability and accuracy of ANN- and SVM-based time series models for long-term groundwater level predictions. Comput. Geosci. 90, 144–155. http://dx.doi.org/10.1016/j.cageo.2016.03.002.